International Journal of Analytical, Experimental and Finite Element Analysis (IJAEFEA), Issue. 3, Vol. 3, Dec 2016.
e-ISSN: 2394-5141, p-ISSN: 2394-5133, pp 36-40

Design and Simulation of Non-linear Adaptive Filters to Forecast Air Pollution

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Abstract—**Due to the modern living style, Industrialization and growth of vehicles on the road air pollution is becoming a major problem especially in Urban and Metropolitans cities. If correct & accurate prediction & precautions are taken for the air polluting components then it can be controlled to some extent. Here the previous values of air polluting components are used as knowledge base which is obtained based on 3 seasons i.e. (summer, winter, rainy). Using the Non-Linear Adaptive filtering and Artificial Neural Network (ANN) the prediction of particular day is made.**

Index Terms— Artificial Neural Network (ANN)

I. INTRODUCTION

The biggest problem of urban areas is air pollution. Air pollution arises from a variety of contaminants emitted into the atmosphere by natural and man-made processes such as industrial emissions, fixed combustions and vehicular traffic. Air pollution requires the analysis and implementation of automatic operating procedures in order to prevent the risk for the principal air pollutants to be above the alarm thresholds. The analysis is based on the medium-term forecasting of the air pollutants, mean and maximum values by means of meteorological actual and forecasted data. Critical air pollution occurs when the geographical and meteorological conditions do not permit an easy circulation of air and a large part of the population moves frequently between distant places of a city

The analysis was performed on the hourly data of the principal air pollutants (Sulphur Dioxide SO2, Nitrogen Dioxide NO2, Nitrogen Oxides NOx, Carbon Monoxide CO, Ozone O3 and Particulate Matter PM10) and meteorological parameters (air temperature, relative humidity, wind velocity and direction, atmospheric pressure and solar radiation)

Our analysis carries on the work already developed by the NeMeFo (Neural Metro Forecasting) research project for meteorological data short-term forecasting. Special attention is devoted to the selection of optimal, non-redundant features from meteorological and air pollution data, decisive to describe the evolution of the system.

Feature selection is based on the partial mutual information (PMI) criterion. Once selected decisive features, prediction is performed using an Artificial Neural Network (ANN). ANNs have been used as a prognostic tool to predict the future air pollutants concentrations.

II. LITERATURE SURVEY & METHODS

A. Steps used to develop an adaptive local prediction tool:

i. Measurement of information on the investigated environment through specific sensors.

ii. Pre-processing of raw time-series data (to reduce noise content or to extract optimal features).

iii. Selection of a model representing the dynamics of the investigated process.

iv. Choice of optimal parameters of the model in order to minimize cost functions measuring the error in forecasting the data of interest the mean square error is usually chosen as cost function.

v. Validation of the prediction, which possibly guides the selection of an alternative model.

B. Training of Non-linear Filter

In figure 1 some of the state variables of the real system are measured and linearly filtered in order to reduce noise or to remove undesired trends & then processed and essential features are selected [1]. The ANN processes such features and produces a prediction which is compared with the actual value of the variable[2]. The prediction error guides update the weights in order to optimize the prediction [11].

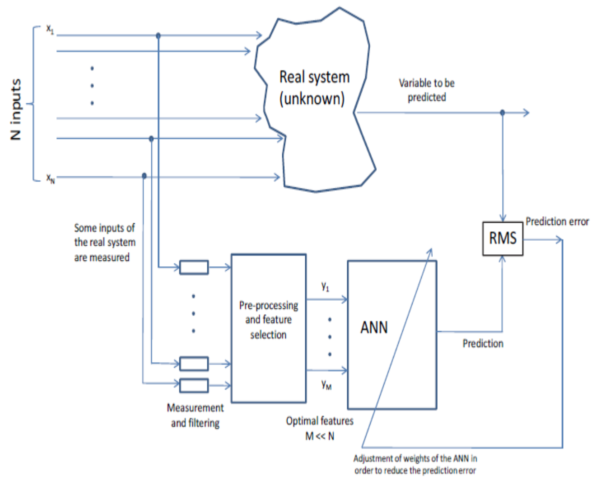

Figure 1. Traning of Non linear filter

C. CO Air Pollution Sensor

CO is a colorless and odorless gas, toxic for human health. CO is mainly discharged in the atmosphere by petrol fumes, as well as from steelworks and refineries, whose energy processes don't achieve complete carbon

combustion. This pollutant is particularly dangerous because of its higher affinity for hemoglobin than oxygen. This could determine hypoxia in CO poisoning. High levels of CO generally occur in areas with heavy traffic congestion [3] as shown in figure 2.

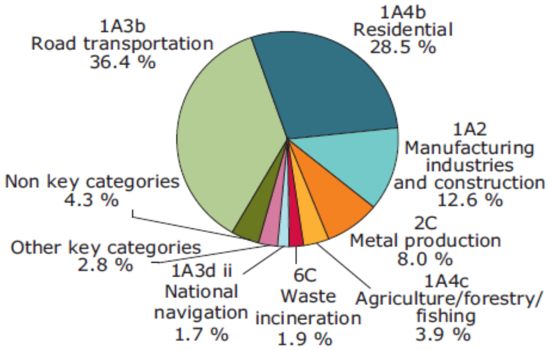

Figure 2: Plot of CO Air Pollution Sensor

D. NO_x Air Pollution Sensor

NO_x forms quickly from volcanic, thunderstorm activity and from emission by vehicles and Power plants. VOCs are organic compounds & are not toxic, but they cause long term chronic health effect as reduction in visual or audible senses [4] as shown in figure 3.

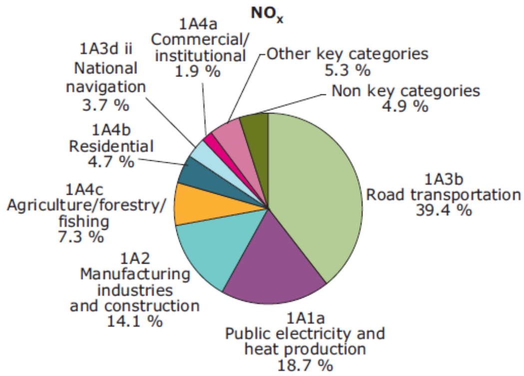

Figure 3: Plot of NO_x Air Pollution Sensor

E. SO_x Air Pollution Sensor

Traditionally, measures designed to reduce localized ground-level concentrations of sulfur oxides (Sox) used high-level dispersion. Although these measures reduced localized health impacts, it is now realized that sulfur compounds travel long distances in the upper atmosphere and can cause damage far from the original source. The extent to which Sox emissions harm human health depends primarily on ground-level ambient concentrations, the number of people exposed, and the duration of exposure [10] as shown in figure 4.

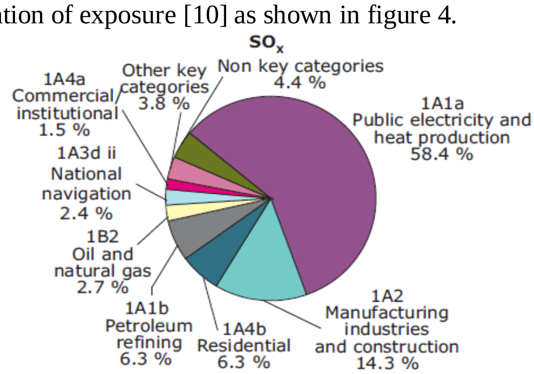

Figure 4: Plot of SO_x Air Pollution Sensor

F. PM_{10} Air Pollution Sensor

Particulate matter (PM) is a complex mixture of extremely small particles and liquid droplets. PM can be primary or secondary. Particle pollution is made up of a number of components, including acids (such as nitrates and sulfates), organic chemicals, metals, and soil or dust particles. Such powders are constituted from various pollutants, as lead, nickel, copper, cadmium and asbestos. They are easily inhaled and, depending on their dimension, they can reach and intoxicate various levels of breathing apparatus, down to alveolus, where the oxygen enhancement of hemoglobin occurs [7] as shown in figure 5.

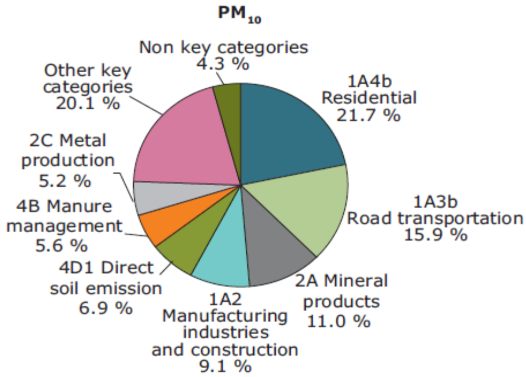

Figure 5: Plot of PM10 Air Pollution Sensor

G. Ozone (O_3) Air Pollution Sensor

Ozone (O_3) is naturally present in the stratosphere portion of the atmosphere around 12000 up to 45000 m ASL where it acts as a filter to block hazardous ultraviolet radiations. O_3 density is highest at around 25000 m ASL in the ozonosphere, the low stratosphere. Thus the troposphere is not affected from the whole solar radiation load that impacts on the ozonosphere. Though the concentration of troposphere ozone is controlled by stratosphere-troposphere exchange, in situ photochemical ozone formation plays an increasing role, especially in urban and industrial areas. At ground-level O_3 is a secondary pollutant. It is linked with adverse effects on the respiratory system (bronchitis, allergic asthma, and irritations up to pulmonary edemas) and irritates mucous. [8] At ground level ozone is created as a byproduct of the oxidation of carbon monoxide (CO) and hydrocarbons. These chemicals are called ozone precursors, and are often emitted simultaneously in the atmosphere via vehicle exhaust, industrial emissions, and other manmade sources[12].

H. Inverse Modeling

We now consider the general problem of inverse modeling as shown in Fig 6. In this diagram, a source signal s (n) is fed into an unknown system that produces the input signal x (n) for the adaptive filter. The output of the adaptive filter is subtracted from a desired response signal that is a delayed version of the source signal such that

$$d(n) = s(n-\Delta)$$

Where, Δ is a positive integer value. The goal of the adaptive filter is to adjust its characteristics such that the

output signal is an accurate representation of the delayed source signal [5] as shown in figure 6.

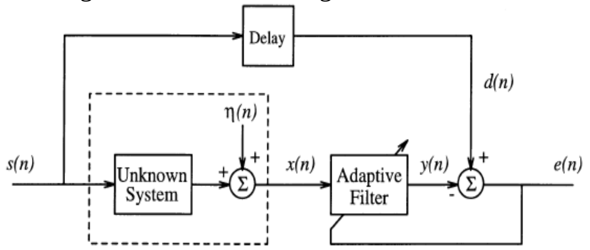

Figure 6: Inverse Modeling

I. Feed forward Control

Another problem area combines elements of both the inverse modeling and system identification tasks and typifies the types of problems encountered in the area of adaptive control known as feed forward control [9]. Figure 7 shows the block diagram for this system, in which the output of the adaptive filter passes through a plant before it is subtracted from the desired response to form the error signal. The plant hampers the operation of the adaptive filter by changing the amplitude and phase characteristics of the adaptive filter's output signal as represented in e (n). Thus, knowledge of the plant is generally required in order to adapt the parameters of the filter properly.[6]

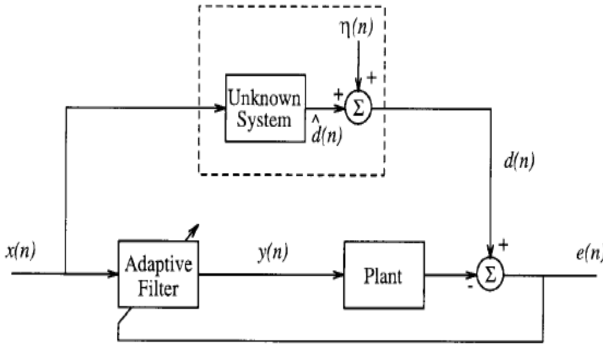

Figure 7: Feed forward Control

III. Results

Forecasting air pollution using non-linear adaptive filter is a generic control loop feedback mechanism widely used in predicting the future air pollution concentration using past predicted pollution concentration as input by taking data's from urban and sub urban areas and in metropolitan's cities. Adaptive algorithm is the most commonly used feedback controller. Adaptive neural network calculates an "error" value as difference between the predicted value and the desired target value. The adaptive neural network attempts to minimize the error by adjusting the weights of different parameters using adaptive algorithm. This process continues until our prediction is close to the desired target value. In this project initially we have to design Adaptive filter based on neural network architecture. Finally we should compare the desired target output and our predicted output to show the performance analysis and prediction error in the MATLAB software.

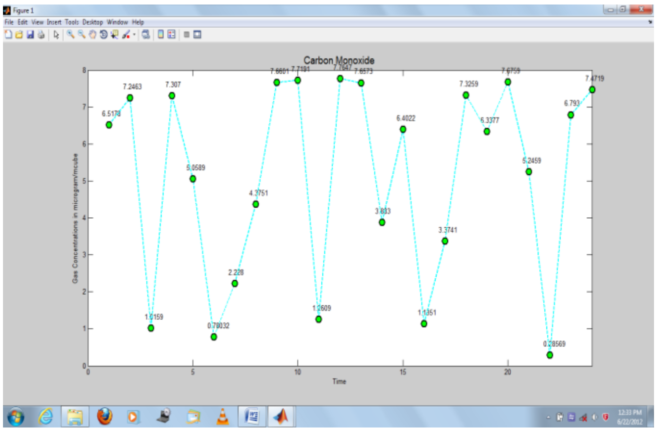

Figure 8: Monitoring air pollution data for CO Sensor

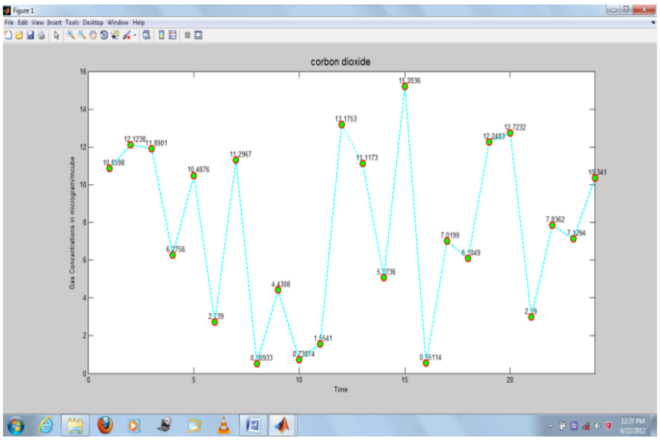

Figure 9: Monitoring air pollution data's for CO_2 Sensor

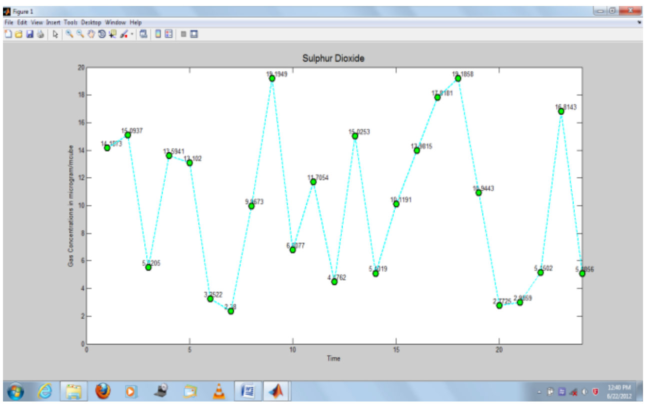

Figure 10: Monitoring air pollution data for SO_2 Sensor

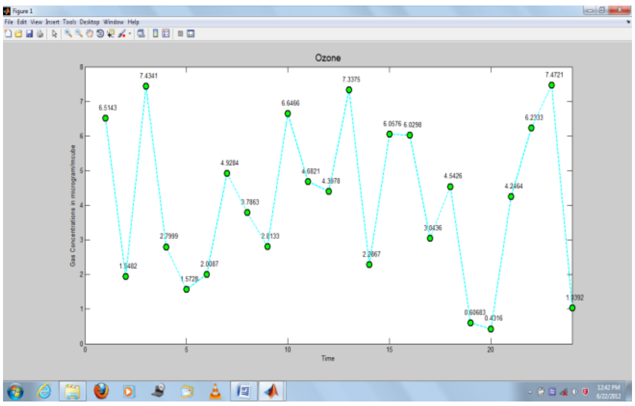

Figure 11: Monitoring air pollution data for O_3 Sensor

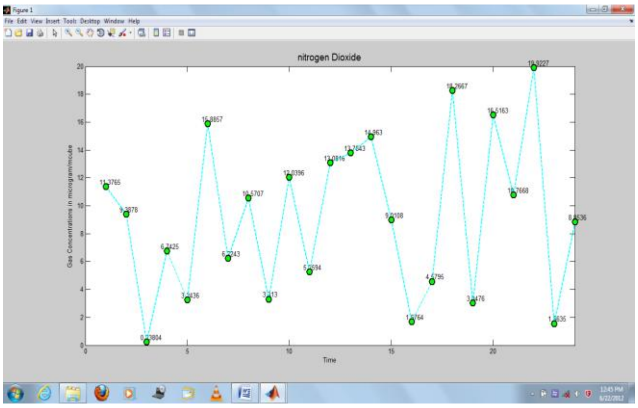

Figure 12: Monitoring air pollution data's for NO_2 Sensor

IV. PERFORMANCE ANALYSIS GRAPH, PREDICTION ERROR GRAPH AND PREDICTION ACCURACY

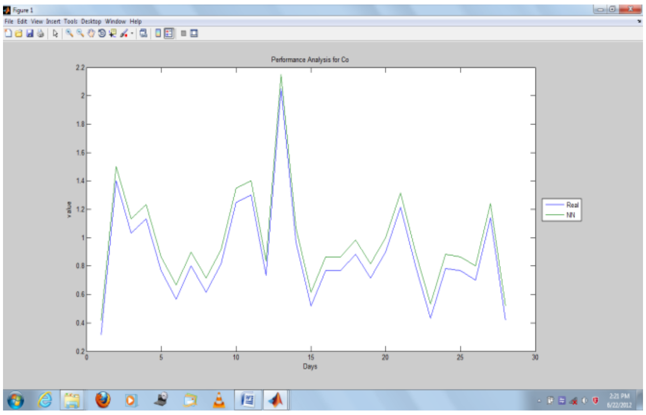

Figure 13: Performance of CO

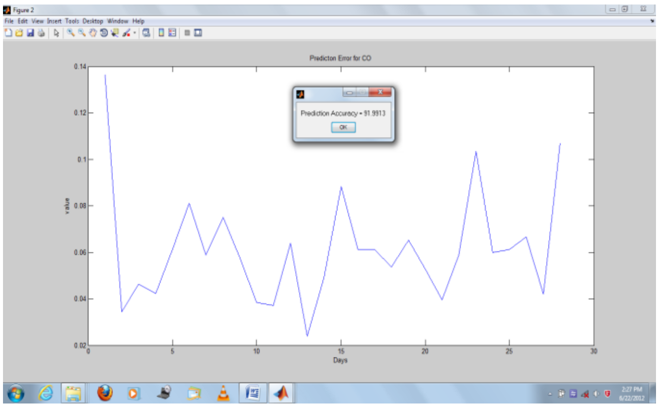

Figure 14: Prediction Error Graph and Prediction Accuracy CO

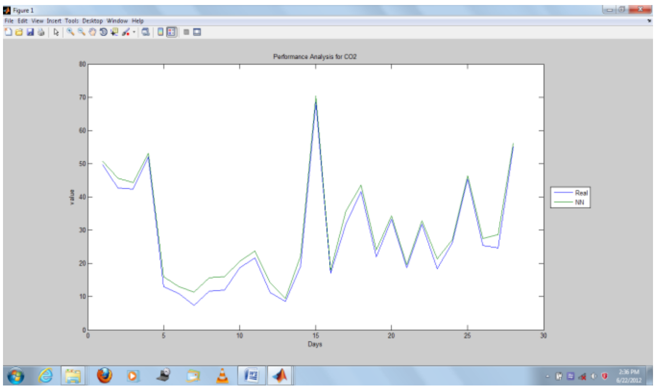

Figure 15: Performance of CO_2

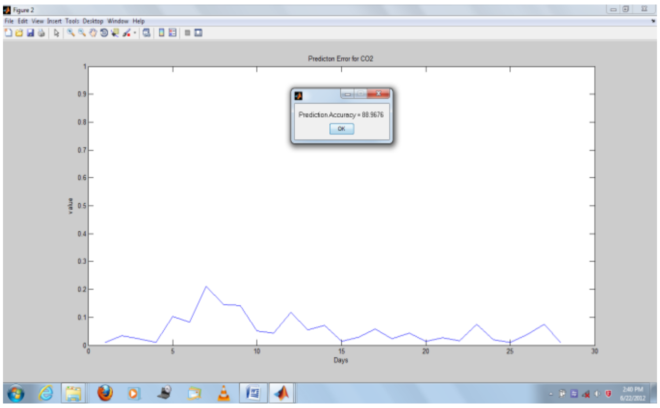

Figure 16: Prediction Error Graph and Prediction Accuracy CO_2

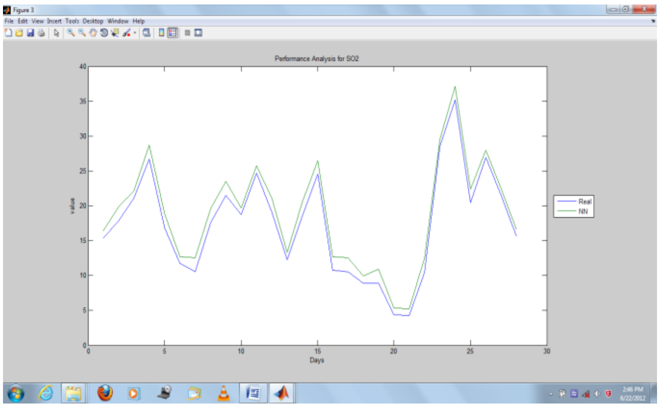

Figure 17: Performance of SO_2

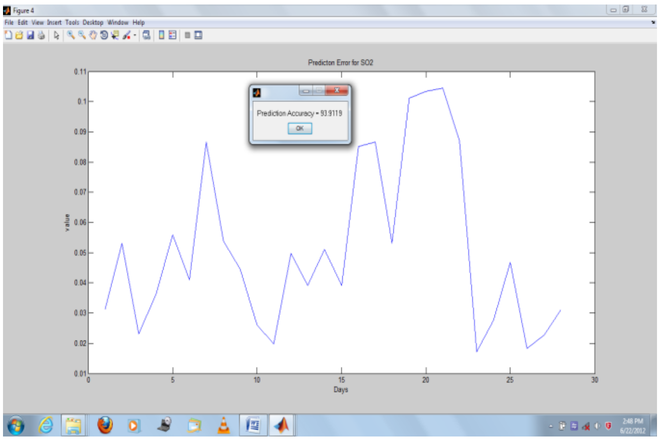

Figure 18: Prediction Error Graph and Prediction Accuracy SO_2

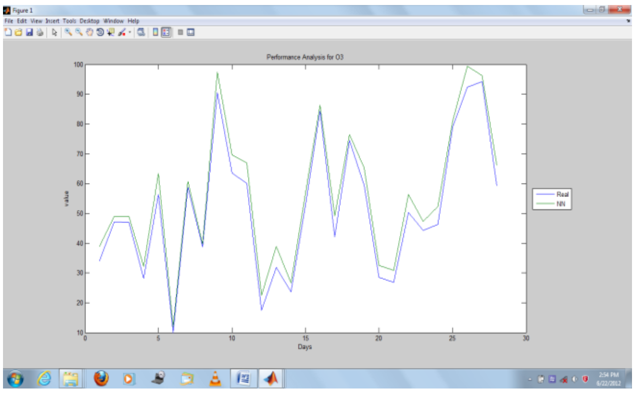

Figure 19: Performance of O_3

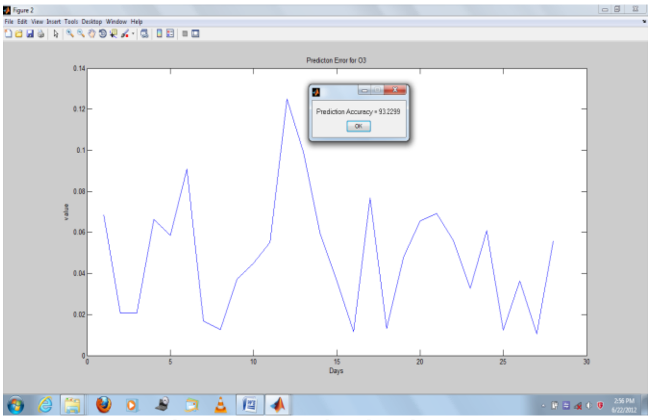

Figure 20: Prediction Error Graph and Prediction Accuracy O_3

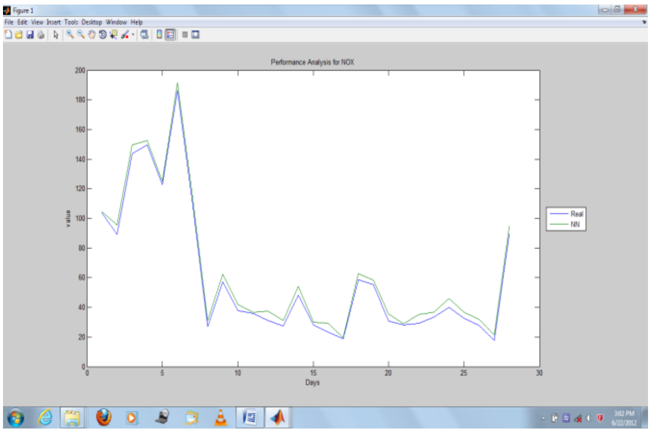

Figure 21: Performance of NO_X

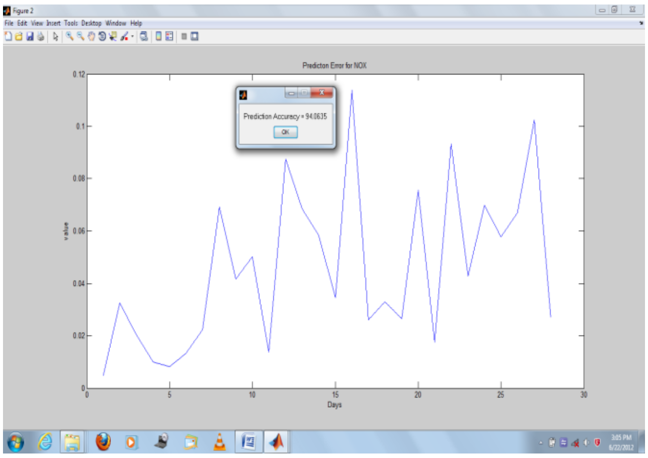

Figure 22: Prediction Error Graph and Prediction Accuracy NO_X

V. Conclusion

The forecasting accuracies are satisfactory and the values of correlation coefficients are more than 94%. The accuracies of predicting are evaluated by calculating RMSE. Annual air pollution time series analysis of New Delhi has been performed in this study and has shown different temporal behavior of different air pollutants. This different time behavior is not only the reason of correlation of different pollutants with each other, but the seasonal variation on increasing or decreasing air pollutants as well. It was also shown that most annual air pollution time series have high persistence of air pollution conditions through time. This persistence is not only harmful for public health but also makes air pollution management and control very demanding.

VI. Acknowledgment

We take this opportunity to thank our college for their valuable guidance and support for getting the good results and providing the software's for the analysis.

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